

Tweeting AI: Perceptions of AI-Tweeters (AIT) vs Expert AI-Tweeters (EAIT)

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Abstract

With the recent advancements in Artificial Intelligence (AI), various organizations and individuals started debating about the progress of AI as a blessing or a curse for the future of the society. This paper conducts an investigation on how the public perceives the progress of AI by utilizing the data shared on Twitter. Specifically, this paper performs a comparative analysis on the understanding of users from two categories – general AI-Tweeters (AIT) and the expert AI-Tweeters (EAIT) who share posts about AI on Twitter. Our analysis revealed that users from both the categories express distinct emotions and interests towards AI. Users from both the categories regard AI as positive and are optimistic about the progress of AI but the experts are more negative than the general AI-Tweeters. Characterization of users manifested that ‘London’ is the popular location of users from where they tweet about AI. Tweets posted by AIT are highly retweeted than posts made by EAIT that reveals greater diffusion of information from AIT.

1 Introduction

Due to the rapid progress of technology especially in the field of AI, there are various discussions and concerns about the threats and benefits of AI. Some of these discussions include – improving the everyday lives of individuals (<https://goo.gl/ViLdgV>), ethical issues associated with the intelligent systems (<https://goo.gl/5KlmXk>), etc. Social media platforms are ideal repositories of opinions and discussion threads. Twitter is one of the popular platforms where individuals post their statuses, opinions and perceptions about the ongoing issues in the society (Java et al. 2007; Naaman, Boase, and Lai 2010; Yang and Counts 2010). This paper focuses on investigating the Twitter posts on AI to understand the perceptions of individuals. Specifically, we compare and contrast the perceptions of users from two categories – general AI-Tweeters (AIT) and expert AI-Tweeters (EAIT). We believe that the findings from this analysis can help research funding agencies, organizations, industries who are curious about the public perceptions of AI.

Efforts to understand public perceptions of AI are not new. Recent work by Fast et. al (Fast and Horvitz 2016) conducts a longitudinal study about articles published on AI from New York Times between January 1986 and May 2016 are transformed over the years. This study revealed that

from 2009 the discussion on AI has sharply increased and is more optimistic than pessimistic. It also disclosed that fears about losing control over AI systems have been increasing in the recent years. Another recent survey (Gaines-Ross 2016) conducted by the Harvard Business Review on individuals who do not have any background in technology, stated the positive perceptions towards AI. In contrast, even though online social media platforms are the main channels of communication (Java et al. 2007; Naaman, Boase, and Lai 2010; Yang and Counts 2010), there is no existing work on how and what users share about AI on these platforms. This paper attempts to learn the perceptions of individuals manifested by their posts shared on Twitter.

Towards this goal, we attempt to answer 5 important questions through a thorough quantitative and comparative investigation of the posts shared on Twitter. 1) What are the insights that could be learned by characterizing the individuals and their interests who are making AI-related posts? 2) What is the Twitter engagement rate for the AI-tweets? 3) Are the posts about AI optimistic or pessimistic? 4) What are the most interesting topics of discussion to the users? 5) What can we learn about the frequently co-occurring terms with AI vocabulary? We address each of these questions in the next few sections.

Our analysis reveals intriguing differences between the posts shared by AIT and EAIT on Twitter. Specifically, this analysis reveals four interesting findings about the perceptions of individuals who are using Twitter to share their opinions about AI. Firstly, users from both the categories are emotionally positive (or optimistic) towards the progress of AI. Secondly, even though users are positive overall, users from EAIT are more negative than those from AIT. Thirdly, we found that the tweets shared by EAIT have lower diffusion rate than the tweets posted by AIT as measured by the magnitude of retweets. Fourth, and last, users from AIT are geographically distributed (mostly Europe and US) with London and New York City taking the top positions.

In the next section, we describe the process of collecting data from the two categories of users that we use for the study presented in this paper. We compare and contrast each of the 5 research questions we posed for Twitter users from the two categories. Results of a similar analysis conducted on the AI posts shared on Reddit, is attached as an appendix.

2 Data Collection

2.1 AI-Tweeters (AIT)

We employ the official API of Twitter¹ along with a frequency-based hashtag selection approach to crawl the data from common Twitter users who tweet about AI. We first identify an appropriate set of hashtags that focus on the artificial intelligence in social media. In our case, these are – #ai and #artificialintelligence. With these seed hashtags, we crawled 2 million unique tweets. Using the hashtags presented in these tweets, we iteratively obtained the co-occurring hashtags and sort them based on their frequency. We remove non-technical hashtags included in this sorted hashtag list for example: #trump, #politics, etc. The top-15 co-occurring hashtags after the pre-processing are shown in Table 1.

1. #ai	2. #artificialintelligence	3. #machinelearning
4. #bigdata	5. #iot	6. #deeplearning
7. #robotics	8. #datascience	9. #cybersecurity
10. #vr	11. #ar	12. #nlp
13. #ux	14. #algorithms	15. #socialmedia

Table 1: Top-15 co-occurring hashtags with the seed hashtags: #ai and #artificialintelligence

We used the top-4 hashtags from this list: #ai, #artificialintelligence, #machinelearning and #bigdata as the final hashtag set to crawl a set of 2.3 million tweets. In our dataset we found that the set of tweets obtained using these 4 hashtags are the super set of all the tweets crawled by utilizing the remaining hashtags presented in Table 1. Each tweet in this dataset is public and contains the following post-related information:

- tweet id
- posting date
- number of favorites received
- number of times it is retweeted
- the url links shared as a part of it
- text of the tweet including the hashtags
- geolocation if tagged

A tweet may contain more than a single hashtag. From this set of tweets, we remove the redundant tweets that have more than one of these four hashtags we considered. This resulted in a dataset of 0.2 million tweets that are unique and are posted by a unique set of 33K users. Due to the download limit of the Twitter API, all the tweets in our dataset are from February 2017, and none of the tweets we crawled were tagged with a geolocation.

2.2 Expert AI-Tweeters (EAIT)

The team at IBM Watson has recently shared an article (<https://goo.gl/PdRIHT>) listing 30 people in AI as “AI Influencers 2017”. This article suggested that these are the top-30 people in AI to follow on Twitter to get updated information about AI. For the purposes of our investigation, we contacted the author of this article through a private email to learn the approach used to compile this list. According to

¹<https://dev.twitter.com/overview/api>

Metric	AIT	EAIT
Mean	10.9 (67.1)	13.96 (72.9)
Median	14 (89)	15.0 (77.0)
Min.	1 (1)	1 (1)
Max.	28 (129)	46 (126)

Table 2: Statistics about the number of words in a post (and number of characters in a post) crawled from Twitter for AIT vs EAIT

the author, this list was compiled by using a combination of thought leaders that the author’s team was aware of. This list includes – AI experts who are most active on Twitter, influencers who speak regularly and present research at AI events & conferences, and entrepreneurs in the AI space who are working on interesting products and technology. The IBM team also interviewed multiple experts to ask them who they follow on Twitter to stay updated on the trending news about AI. Table 3 enlists the AI Influencers 2017 named by this article (sorted alphabetically). We then utilize the Twitter official API to crawl the timelines of these 30 AI influencers.

Nathan Benaich	Joanna Bryson	Alex Champandard
Soumith Chintala	Adam Coates	The CyberCode Twins
Jana Eggers	Oren Etzioni	Martin Ford
Adam Geitgey	John C. Havens	J.J. Kardwell
David Kenny	Tessa Lau	Dr Angelica Lim
Satya Mallick	Gary Marcus	Chris Messina
Elon Musk	Dr Andy Pardoe	Alec Radford
Delip Rao	Dr Roman Yampolskiy	Gideon Rosenblatt
Adam Rutherford	Matt Schlicht	Murray Shanahan
Amir Shevat	Rest Sidhu	Adelyn Zhou

Table 3: Top-30 AI Influencers 2017 enlisted by IBM

3 RQ1: Characterization of Users

Before we delve deep in to investigating the research questions posed earlier, we present few details about the demographics of users from both the categories. We first focus on the influence attributes of users – #statuses shared, #followers, #friends, #favorites. To understand the differences between the two types of user categories based on their activity and influence of tweets, we plot the logarithmic frequencies of these attributes in Figure 1. Surprisingly, the influence attribute values of experts are significantly lower than the general Twitter users.

Figure 1 shows that both sets of users are highly active on Twitter by sharing statuses and favoriting tweets. When we consider the other influence attributes – followers and friends, on an average both sets of users have large number of followers than friends (users you are following). The statuses shared by EAIT are approximately equal to the number of favorites. However, AIT share more number of statuses than favoriting other tweets. This observation also suggests that the users in AIT and EAIT are active on Twitter as user activity is influential in attracting more number of followers (Bakshy et al. 2011).

Table 2 compares the statistics about the length of posts made by AIT and EAIT. On average, EAIT’s tweets are

Attributes of Users -- Twitter Users vs Experts

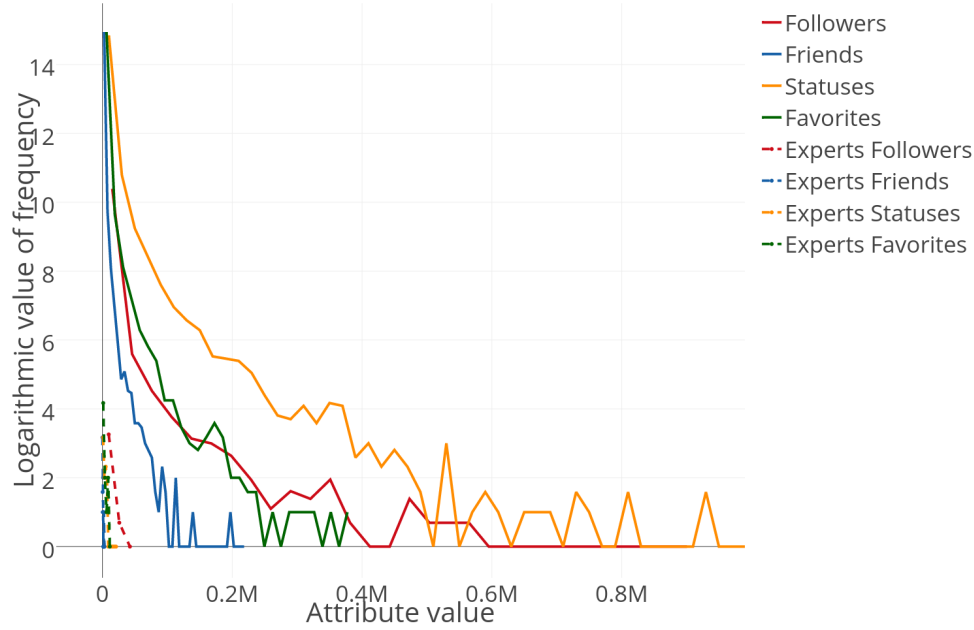


Figure 1: User attributes – Followers; Friends; Statuses; Favorites. The plain lines correspond to the Twitter users and the dotted lines correspond to the experts. X-axis represents the attribute’s value where as, Y-axis represents the logarithmic value of the frequency

longer compared to the tweets posted by AIT. We then looked in to the particulars of the users’ geographical location and professional background which we obtained from their biography profiles. Figure 2 shows that the highest percentage of users in our dataset who tweet about AI are from London (6% of the total set of users) followed by New York City (4%) and Paris (3%). The histogram shows only the top-10 locations of users as we also have a fair percentage of users tweeting from locations such as Sydney (1%), Berlin (0.98%), etc. Where as from EAIT, large percentage (14%) of users in this set do not provide their geographical location. However, the top-2 locations of experts are San Francisco (10%) followed by Seattle (7%).

We conducted a unigram-based analysis of the profiles of the users to decipher their professional background. Table 4 shows that based on the frequencies of professions stated by users on Twitter, majority of the Twitter users contributing to AI-related tweets are pursuing careers in technology.

User Category	Occupation
AIT	entrepreneur, director, manager, enthusiast, founder, consultant, ceo, author, leader, engineer
EAIT	scientist, author, ceo, director, entrepreneur, co-founder, expert, researcher, technologist, professor

Table 4: Top-10 occupations extracted from the user biographies

3.1 User Interests

To examine the interests of the users in our dataset, we crawled the recent 100 posts made by these users. We extract the topics from these posts made by users using the Twitter LDA package (Zhao et al. 2011). By utilizing these topics, we aim to measure the level of users’ interest in technology which can quantify their perceptions about AI.

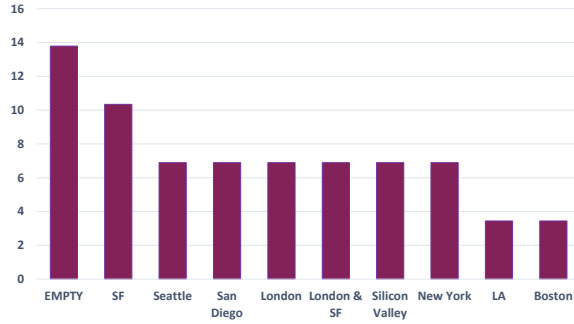
AIT As mentioned earlier, there are a total of 33K unique set of users who contributed towards our dataset. We crawl their recent tweets to extract the topics. We empirically decided to extract 5 topics and their corresponding vocabulary are shown as below:

- Topic-1** [Science & Technology]: data, learning, intelligence, business, machine, digital, analytics, cloud, trends, science
- Topic-2** [Personal Status & Opinions]: people, time, day, good, love, today, life, work, happy, story
- Topic-3** [General News]: latest, stories, daily, join, great, world, march, live, week, day, event, network, news
- Topic-4** [Non-English Tweets]: pour, les, des, para, los, dans, qui, avec, une, se, las
- Topic-5** [Daily Updates]: follow, daily, chapter, updates, translation, card

By considering the topics, we obtain the percentage distribution of each individual’s tweets to these 5 different topics. We then aggregate all the distributions of users across these



(a) Twitter Users



(b) Experts

Figure 2: Top-10 locations of users. Horizontal axis represents the location; vertical axis represents the percentage of users who are situated at a given location

topics and the percentage distributions are shown in Figure 3. This figure shows that majority of the tweets posted by the users are about technology and science.

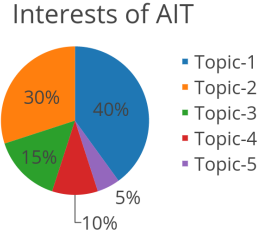


Figure 3: Topic Distributions Extracted from Twitter. Topic-1: Science & Technology; Topic-2: Personal Status & Opinions; Topic-3: General News; Topic-4: Non-english Tweets; Topic-5: Daily Updates

EAIT We conduct a similar investigation as above on the tweets posted by experts. The topics extracted and their corresponding vocabulary are shown here:

1. **Topic-1** [Rise of AI]: robots, intelligence, jobs, future, human, tesla, cars, driving, learning, machine
2. **Topic-2** [AI subscriptions and research]: papers, news, subscribing, events, latest, learning, deep, code, work, image, model, people

3. **Topic-3** [AI News from industry]: zapchain, google, sharing, bitcoin, startup, slack, twitter, working, app, facebook, medium, chatbots
4. **Topic-4** [Marketing & AI]: virtualreality, ibmwatson, team, marketing, virtual, work, channel, bit, time
5. **Topic-5** [Opinions about AI]: essays, tweeting, enjoy, visit, brain, neuroscience, conspiracy, cleaning, fiction, theory, fun, hype, post

These topics reveal that experts predominantly focus on posting about AI, its impacts, industry aspects of AI, their opinions and subscription recommendations which may help provide more information about AI. These topics are different from the topics focused by AIT. The pie chart shown in Figure 4 reveals that more than 50% of the tweets posted by experts on Twitter are about the impacts of AI and research directions in this field. AIT share large percentage of personal opinions and statuses where as EAIT post the least percentage of tweets about their opinions.

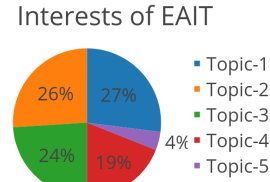


Figure 4: Topic Distributions Extracted from Twitter. Topic-1: Rise and impact of AI; Topic-2: AI subscriptions and research; Topic-3: AI News from industry; Topic-4: Marketing & AI; Topic-5: Opinions about AI

4 RQ2: Twitter Engagement

We seek to study the attributes which might disclose the holistic picture of the overall engagement rate of AI-related tweets. This rate provides us with an information on patterns of public interests and perceptions in AI. We measure the engagement by considering the ‘favorites’, ‘likes’, ‘replies’ and ‘mentions’ of a Twitter post. We first compute Twitter engagement statistics that are shown in Table 5.

	Min (Max)		Median (Mean)	
	AIT	EAIT	AIT	EAIT
Retweets	0 (3364)	0 (31297)	2.0 (19.38)	0.0 (39.61)
Favorites	0 (69)	0 (109569)	0.0 (0.12)	1.0 (97.79)
Mentions	0 (10)	0 (12)	1.0 (1.05)	1.0 (0.97)

Table 5: Min (Max) and Median (Mean) values of Retweets, Favorites, Mentions

Tweets made by AIT are more likely to be retweeted than favorited by the users on this platform. 63.3% of their tweets are retweeted atleast once. This is significantly higher than the general dataset which is 11.99% as shown by the existing literature (Suh et al. 2010). Where as, the tweets posted by EAIT received more number of favorites than retweets as only 35% of the tweets are retweeted atleast once.

Tweets from both the categories of users have higher probabilities of containing atleast one user handle. This may suggest that users are more likely to interact or engage in discussions with each other about AI on Twitter. On the other hand, 68.5% of the tweets posted by AIT in our dataset have atleast one url shared as part of the tweet where as 48% of the tweets made by EAIT have urls. Sharing large percentage of urls by AIT compared to EAIT could be one of the reasons for receiving more retweets than favorites. Literature (Java et al. 2007; Kwak et al. 2010; Yang and Counts 2010) considers retweeting as one of the features to measure information diffusion. Based on these results, tweets posted by AIT diffuse faster (higher retweet rate) than the tweets posted by EAIT.

5 RQ3: Optimistic or Pessimistic

Optimism is defined as being hopeful and confident about the future whose synonym is ‘positive’ and pessimism is defined as tending to see or believing that the worst will happen whose synonym is ‘negative’. In this work we measure these two attributes – positive, negative emotions alongside assessing cognitive mechanisms by employing the popular psycho-linguistic tool LIWC (Tausczik and Pennebaker 2010). Tausczik et. al in their work introducing LIWC mention that the way people express emotion and the degree to which they express it can tell us how people are experiencing the world. Existing literature (Danescu-Niculescu-Mizil, Gamon, and Dumais 2011; Tsur and Rappoport 2012; Tumasjan et al. 2010) states that LIWC is powerful in accurately identifying emotion in the usage of language. This is the motivation for us to use LIWC to measure the emotionality of tweets shared by AIT and EAIT.

5.1 AIT

Figure 5 reveals that individuals are more positive (65% greater than negative) and optimistic towards AI and its related topics. This concurs with the recent analysis (Fast and Horvitz 2016) and survey (Gaines-Ross 2016) on New York Times articles and interviews with individuals respectively. This is a useful finding because Twitter is known for users making posts that are emotionally negative (Manikonda, Meduri, and Kambhampati 2016). In other words, despite the general negative emotional content on Twitter, this subset of tweets focusing on artificial intelligence are more positive than being negative.

5.2 EAIT

We conduct the emotion analysis on tweets posted by experts and it reveals similar findings as earlier (shown in Figure 6) but with relatively higher cognitive mechanisms than AIT. Cognitive mechanisms or complexity can be considered as a rich way of reasoning (Tausczik and Pennebaker 2010). The horizontal axis represents the gravity of a given emotion and the vertical axis represents the number of posts with a gravity value shown on horizontal axis. The distribution in each plot are normalized and the sum of all the values in different buckets of gravity will sum upto 100%.

Compared to AIT, tweets made by EAIT have more negativity overall. However, positive emotion is thrice as dominating as the negative emotion. When we compare the positive and negative emotions of the two categories of users, the results reveal that expert users are 38% more negative than the general AI-Tweeters.

6 RQ4: Topics heavily discussed by users on Twitter

In Section 3.1, we have presented the analysis on the interests of users by crawling their timelines and extracting topics from these timelines. In order to better understand the public perceptions about AI, we extract topics from the tweets that are exclusively about AI.

To perform this, we first consider all the tweets posted by AIT using the hashtag approach. In Table 6, we present the topics extracted by considering the aggregated set of tweets. These topics display that the focus of the AI-tweets are on stories and statistics about AI followed by discussions about deep learning. These topics reveal the high-level interests of individuals about the emerging trends, impacts and career opportunities related to AI.

These topics also display that individuals have continued interests in the similar topics over years due to partial alignment of these topics with the findings shown by Fast et. al (Fast and Horvitz 2016) who consider NYT articles published before 2017. We perform this analysis on the AI-tagged tweets from Twitter as we assume that this set may comprise both experts and general Twitter users.

7 RQ5: Co-occurring concepts discussed

The questions we investigated until now provides valuable insights into whether and how individuals perceive the issues about AI advancements. However, we note that conceptual relationships could significantly quantify and measure the perceptions of individuals. Towards addressing this challenge, we employ the popular word2vec analysis to detect relationships between words that are frequently co-occurring. Word2Vec (Mikolov et al. 2013) is a popular two-layer neural network that is used to process text. It considers a text corpus as an input and generates feature vectors for words present in that corpus. Word2vec represents words in a higher-dimensional feature space and makes accurate predictions about the meaning of a word based on its past occurrences. These vectors can then be utilized to detect relationships between words which are highly accurate given enough data to learn these vectors.

To detect the relationships, we train the Word2Vec model on the *Text8* corpus (<http://mattmahoney.net/dc/>) which is created using the articles from Wikipedia. As a processing step, we first remove stop words from the tweets and consider each tweet independently. We utilized the pre-existing lists from academia² and industry³ to manually compile the AI vocabulary of 61 words. Figure 7 provides two pairs of co-occurring pattern comparisons. These

²<https://www.cs.utexas.edu/users/novak/aivocab.html>

³<http://www.techrepublic.com/article/mini-glossary-ai-terms-you-should-know/>

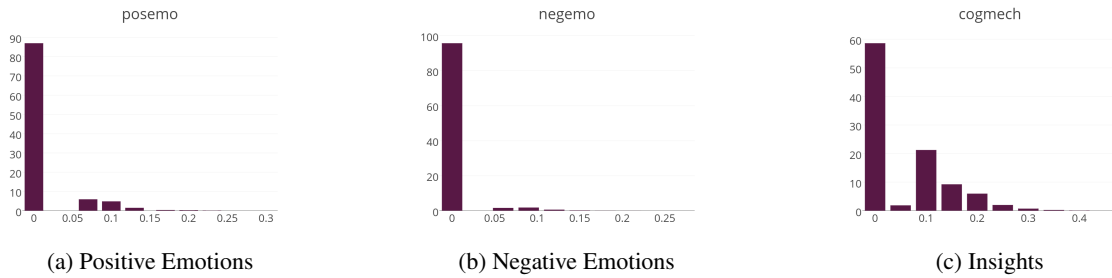


Figure 5: Emotions from the tweets posted by AIT

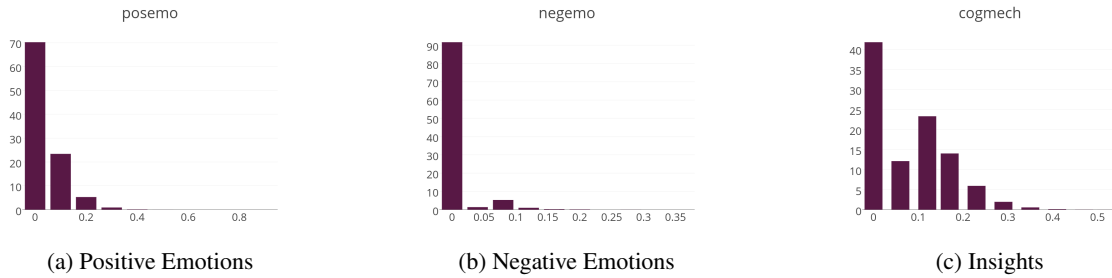


Figure 6: Emotions from the tweets posted by EAIT

ID	Topic	Top Tags	% of tweets
1	Stories & Statistics	future, stories, problems, statistics, analytics	13.8%
2	Deep learning	deeplearning, deep, neuralnetworks, tensorflow, human	12.2%
3	Emerging trends	trends, 2017, iot, machinelearning, vr, ar	11.7%
4	Applications	cars, robotics, healthcare, startups, banking	11.43%
5	Lessons & learnings	guide, cloud, healthcare, lessons, rstats	10.4%
6	Impact & predictions	chatbots, world, impact, influence, predicts	8.87%
7	Applications & impact of AI	chatbots, cancer, robots, jobs, automation	8.5%
8	Jobs & recruitment	experts, marketing, hiring, consulting, experience	8.3%
9	Business & revenue	innovation, growth, companies, revenue, startup	7.6%
10	Big data & data science	analytics, bigdata, datascience, innovation, smart	7.2%

Table 6: 10 topics and the corresponding vocabulary extracted along with the percentage distribution of tweets across these topics.

pairs of co-occurring patterns tell us that AIT are in general fantasizing about the future where as EAIT are grounded and realistic. The entire list of co-occurrences for the 61 words in AI vocabulary can be found here: AIT (<https://goo.gl/5WPA9L>) and EAIT (<https://goo.gl/8WxBaP>).

8 Conclusions

Social media platforms are one of the primary channels of communication in the lives of individuals. These platforms are reshaping our ideas and the way we share those ideas. Given the increasing interest in AI from different communities, multiple debates are commencing to evaluate the benefits and drawbacks of AI to humans and society as a whole. This paper presents the findings from our investigation on public perceptions about AI using the AI-related posts shared on Twitter. Alongside, we performed a comparative analysis between how the posts made by AIT and EAIT are engaged. Some of the key findings from our analysis are:

1. Tweets about AI are overall more positive compared to

the general tweets.

2. Tweets posted by experts are more negative than the general AI tweeters.
3. Tweets posted by experts have lower diffusion than the tweets posted by general AI tweeters.
4. General AI-tweeters are geographically distributed with London and New York City as the top locations.

The co-occurring pattern mapping tells us that users belonging to EAIT are more grounded and realistic in their perceptions about AI. Additionally, analysis on user interests revealed that tweeters who are posting about AI are interested in technology. The most discussed topics on Twitter by the general AI tweeters are about the *stories and statistics* alongside the impact of deep learning, career and recruitment aspects. Our LIWC analysis revealed that discussions are cognitively loaded with a larger variance of gravities among Twitter users.

We hope that our findings will benefit different organiza-

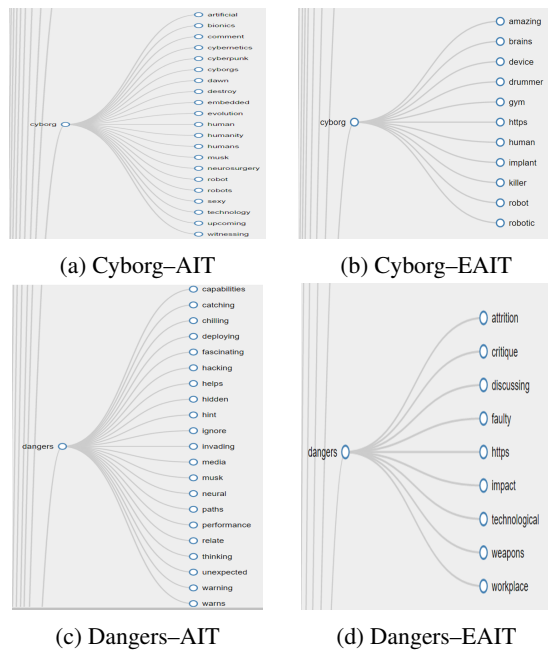


Figure 7: Co-occurring patterns. The word on the left belongs to the AI vocabulary which is mapped to multiple words that are used by the users in their tweets about AI.

tions and communities who are debating about the benefits and threats of AI to our society. Some of the future directions include a longitudinal study across several years as well as multiple mediums of communication.

8.1 Acknowledgements

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A Appendix – Analysis on Reddit

Reddit is one of the popular online social media platforms that is considered as a social news and a discussion platform. Users on this platform can share posts that may contain either text or media. Other users on this platform can then vote or comment on these posts. There are different sub-communities organized by the areas of interest also called as Subreddits. Posts on any subreddit are of two types – self post or a link post. Self post is defined as a post that contains text and the content of this information is saved on the Reddit’s server. Link post submission redirects the user to an external website. Similar to the Twitter analysis, we consider the subreddits that focus on AI to capture user perceptions about AI. To start the analysis, we match the hashtags used in Twitter analysis to the names of subreddits to conduct a comparative study between Reddit and Twitter. Also, please note that all the users considered for Reddit analysis are categorized as common Reddit users with no distinction between experts and non-experts.

A.1 Data Collection

To crawl the data from Reddit, we employed the Python Reddit API Wrapper ⁴ (PRAW). We utilized the subreddits that focus on the same topics as the hashtags used to crawl the data from Twitter – *r/artificial*, *r/machinelearning* and *r/datascience*. Across the 3 subreddits, a total of 2,550 unique thread posts are crawled from 5 different categories of posts – *hot*, *new*, *rising*, *controversial* and *top*. The total number of posts aggregated across all the threads consists of 21,420 posts.

For each post crawled using PRAW, the metadata includes the title of the post, content of the post, score of the post, up votes, down votes, posting date, username of the author. In our dataset, we have 5,382 unique number of users. For understanding the users and their background, we separately crawl the recent 100 posts made by each individual user on Reddit. The posts we use for our analysis come from the time period between November 2016 until March 2017.

A.2 RQ1: Reddit Engagement

Our first research question explores different set of statistics to understand the engagement on the subreddits related to artificial intelligence. Towards this goal, we first understand whether the posts are questions or opinions. We utilize the ‘wh’ questions along with the post that matches the ‘?’ pattern. 52.8% of the posts we crawled from Reddit related to AI are questions. This suggests that the interest to seek information on Reddit is high.

Each post made on the subreddit can be voted as up or down which also allows users to comment on this post. The score of a post is defined as the sum of up votes and down votes. In our dataset, *there are no posts which have a down vote*. This might be due to the inherent nature of subreddit that we are focusing on. On average, each post received around 20 votes with a median of 7 votes. The post made by Google Brain team encouraging the community to ask questions about machine learning received the maximum number of votes (4196).

⁴<https://praw.readthedocs.io/en/latest/>

A.3 RQ2: Optimistic or Pessimistic

We conduct a similar analysis on Reddit posts, that we have conducted on tweets, to measure the emotional gravity. To do this, we first pre-process the data by considering only the textual content attached to the post that doesn’t consider the title of the post. Similar to the Twitter analysis, we do not remove any stopwords because in the LIWC (Tausczik and Pennebaker 2010) analysis, stopwords may count towards providing emotional insights. Figure 8 shows that, Reddit posts are emotionally more positive than Twitter.

A.4 RQ3: Topics heavily discussed and concerning to the public

Analysis on emotions shows that there is a higher percentage of positive emotions alongside cognitive complexity and expressing insights. To explain this phenomenon, exploring the topics focused in the posts can be beneficial. To do this, we consider the Twitter LDA (Zhao et al. 2011) package and the extracted topics are shown in Table 7. The posts about *data science and careers* are the most discussed topics. We define the *unclassified text* as the non-english text or a post that includes emoticons. However, we also notice that Reddit posts on Reddit focus on various topics of AI – *comparison of intelligent systems with humans* (Topic-6), *properties of intelligent machines* (Topic-7), *how to learn or train these intelligent models* (Topic-8), *neural networks* (Topic-4), *applications like games* (Topic-3), *how industry is spreading its interest around AI* (Topic-5), *future applications* that could be envisioned (Topic-2).

In comparison to Twitter that focuses only on 7.2% of tweets on *data science*, Reddit has higher percentage of posts on this topic. However, 7 of the 9 topics (that constitute 72.1% of the Reddit posts) very tightly focus on the technical details about intelligent systems and their performance. For example – details about training the learning models, properties of intelligence machines, nuances of technicalities from the perspective of industry, emphasizes on technical aspects of AI systems. On the other hand, Twitter topics are relatively skewed in terms of mostly focusing on marketing, recruitment, stories, impact, etc and do not heavily focus on the technical details about the intelligent systems. This might be due to the fact that Reddit as a platform does not have any constraints on the length of the post. This could be one of the reasons why the posts on Reddit focus on in-depth technicalities about the AI systems.

A.5 RQ4: User Analysis

As mentioned earlier, understanding the conclusions we inferred from the Reddit posts could be more valuable if we recognize the interests of users. To understand the background of the 5,382 unique set of Reddit users from our dataset, we crawl their recent 100 Reddit posts.

1. **Topic-1** [Topics about life]: *people, good, pretty, money, games, things, years, lot, high, pay*
2. **Topic-2** [Political issues]: *government, country, world, time, years, women, good, bad, person, life*
3. **Topic-3** [Mobile or Web Applications]: *work, love, great, windows, app, phone, video, version, link, find*

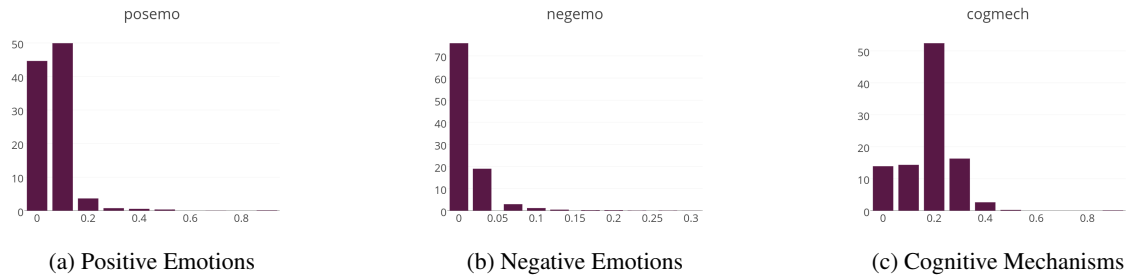


Figure 8: 10 statistically significant emotions and their values measured in the posts made on Reddit

ID	Topic	Top Tags	% of tweets
1	Data science careers	data, math, science, degree, python, statistics, school, phd, stats, scientist	23.3%
2	Future intelligence	human, intelligence, future, neural, brain, create, learning, talking, years, quantum	11.5%
3	Games	people, work, code, game, learns, find, create, play, brain, function	10.2%
4	Neural networks & deep learning	training, network, model, neural, function, layer, train, gradient, batch, weights, images	9.5%
5	Industry & AI	google, system, alphago, brain, world, data, neural, state, memory, tensorflow	9.3%
6	Humans & intelligent machine	human, brain, consciousness, people, intelligence, model, computer, neural, utility, information	9.2%
7	Intelligent machines	humans, system reasoning, algorithm, information, agents, smart, control, turing, robot, intelligence	6.1%
8	Learning & training	model, attributes, data, features, regression, layers, forest, network, function, error	6.0%
9	Unclassified	unclassified	4.6%

Table 7: 9 topics and the corresponding vocabulary extracted along with the percentage distribution of reddit posts across these topics.

4. **Topic-4** [Training neural networks]: *model, code, neural, function, training, network, deep, learn, image*
5. **Topic-5** [Intelligence aspects]: *ai, people, human, brain, work, learning, data, intelligence, understand*
6. **Topic-6** [Jobs and programs offered in Data Science]: *science, python, job, math, experience, programming, courses, statistics, degree, ml*
7. **Topic-7** [External URL shares]: *en.wikipedia.org, www.youtube.com, watch, i.imgur.com, delete,youtu.be, definition*

According to the topic distributions shown in Figure 9, these users are interested in technology – especially neural networks. Eventhough on an average, 44% of the reddit posts made by a user focuses on general topics about *life and politics*, 25% of their posts talk about *training neural networks and intelligence*. This may shed more light on the perceptions of AI that are mainly shared and discussed by users with interests in technology especially related to AI.

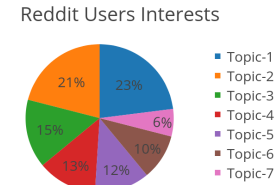


Figure 9: Topic Distributions Extracted from Reddit. Topic-1: Topics about life ; Topic-2: Political issues ; Topic-3: Applications ; Topic-4: Training neural networks; Topic-5: Intelligence aspects; Topic-6: Datascience related Jobs and programs ; Topic-7:External url shares

The main findings from the Reddit analysis are that the users are more optimistic than the users on Twitter. The topic analysis shows the technical depth in to different aspects of AI. This might be due to the nature of Reddit platform that doesn't have restrictions on the length of a post.